



# **Study on Energy consumption of machine tool Processing based on GA-BP algorithm**

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the award of MSc Master of Science

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## Declaration of Originality

I, Jordan Phillips, declare that I am the sole author of this Project; that all references cited have been consulted; that I have conducted all work of which this is a record, and that the finished work lies within the prescribed word limits.

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**Abstract**—With the continuous increase of global use of available energy, the energy crisis and environmental problems brought by energy consumption are becoming increasingly severe. Around the world, people are becoming increasingly concerned about how they can cut their emissions and energy use. Industrial use of available energy accounts for the first place in the global total energy consumption. How to reduce and optimize industrial use of available energy is a key research issue for each country. Machine tool as an industrial mother machine, its use of available energy is large and energy efficiency is low. It is of great significance to reduce the use of available energy of machine tool and improve its energy efficiency. With the development of sensor technology and industrial Internet technology, the process data collected in machining workshop contains rich information. Mining the relationship between process data and use of available energy can provide an effective way to optimize the energy efficiency of CNC machine tools.

The energy usage of the machining process is influenced by the machining settings. By optimizing process parameters at the process planning stage, an industry may save energy by using a credible use of available energy forecast model. Firstly, the grey correlation analysis method is introduced to determine the main factors affecting use of available energy and their influence degree. According to the structure of the use of available energy system of NC machine tool, the factors affecting use of available energy in each period of working condition are analyzed. The power data acquisition platform of CNC machine tool was built, and the orthogonal experiment was carried out to obtain experimental data. Grey correlation analysis method was used to analyze the data. In this experiment, spindle speed, feed speed, cutting depth and cutting width were taken as the main factors affecting use of available energy under the processing condition, and their influence degree was sorted. Secondly, by analyzing the characteristics of BP neural network algorithm and GA algorithm, a modeling method based on GA algorithm ensemble optimization BP neural network is proposed, and the prediction model of GA-BP ensemble algorithm is established, and the feasibility of model prediction is verified by analyzing cutting cases. The model is used to improve the prediction accuracy of machine tool use of available energy under the condition of small sample prediction. Finally, in order to further determine the advantages of BP-BP integrated algorithm prediction model in machine tool use of available energy prediction, BP-GA and traditional BP algorithm model are introduced into use of available energy prediction for comparison and analysis. The results show that the integrated optimized BP-GA algorithm model is more accurate in predicting machine tool processing energy consumption. In this paper, an improved BP neural network algorithm based on genetic algorithm is proposed to predict and characterize the relationship between use of available energy and processing parameters. The BP neural network with a hidden layer is used to verify the model based on the real experimental data. The weight matrix  $W_1, W_2$ , offset value  $B_1, B_2$ , learning rate and the number of training rounds of the BP neural network are taken as the population genotype of the genetic algorithm, and the optimal model parameters are screened by the genetic algorithm. Traditional BP neural network to use gradient descent method for the

optimization of weights and bias, but the object of the gradient descent method is not a simple two-dimensional smooth curve, is often a more complex three dimensional uneven surface, when on the gradient descent method is very easy to fall into local optimal solution, and the local optimal solution often from the optimal solution is large, Does not meet the requirements of the model that researchers want to simulate input and output data. When the optimal parameters purified by genetic algorithm are transferred to the BP neural network, the BP neural network can get a very excellent model. The experimental results show that the model can accurately predict the use of available energy under the given machining parameters, and the accuracy of using the model to predict the use of available energy of machine tools is more than 10% higher than that using BP neural network alone.

This study not only provides a new algorithm model for use of available energy prediction of NC machine tools, but also provides method support for process parameter optimization, and has broad application prospects in energy saving machining of machine tools.

***Keywords: Genetic Algorithm; Artificial Neural Network; Regression Analysis; Intelligent Manufacturing***

## Table of Contents

|                            |    |
|----------------------------|----|
| Chapter 1 .....            | 6  |
| 1.1 Introduction.....      | 6  |
| 1.2 Aims .....             | 9  |
| 1.3 Objectives .....       | 10 |
| Chapter 2 .....            | 11 |
| 2.1 Literature Review..... | 11 |

|                                                                                                 |    |
|-------------------------------------------------------------------------------------------------|----|
| 2.1 Research status of energy consumption of CNC machine tool processing system .....           | 12 |
| 2.1.1 The power consumption at the Device layer is abnormal.....                                | 12 |
| 2.1.2 Study on energy consumption of process layer .....                                        | 13 |
| 2.2 Energy consumption prediction method of CNC machine tool machining system .....             | 15 |
| 2.2.1 Traditional theoretical energy consumption prediction and optimization .....              | 16 |
| 2.2.2 Traditional experimental fitting energy consumption prediction and optimization .....     | 17 |
| 2.2.3 Data-driven energy consumption prediction and optimization based on machine learning..... | 18 |
| Chapter 3 .....                                                                                 | 20 |
| 3.1 Methodology .....                                                                           | 20 |
| 3.2 GA algorithm .....                                                                          | 20 |
| 3.2.1 GA algorithm theory .....                                                                 | 20 |
| 3.2.1 GA algorithm step .....                                                                   | 21 |
| 3.3 BP neural network algorithm .....                                                           | 25 |
| 3.3.1 BP neural network algorithm theory .....                                                  | 25 |
| 3.3.2 BP neural network algorithm step.....                                                     | 26 |
| Chapter 4 .....                                                                                 | 27 |
| 4.1 Data collection .....                                                                       | 27 |
| Chapter 5 .....                                                                                 | 31 |
| 5.1 Design .....                                                                                | 31 |
| 5.1.1Design of energy consumption model of GA-BP algorithm.....                                 | 31 |
| 5.1.2Code design of GA-BP algorithm.....                                                        | 32 |
| 5.2 Implementation .....                                                                        | 36 |
| 5.2.1 Experimental data set.....                                                                | 36 |
| 5.2.2Parameter determination .....                                                              | 37 |
| 5.3Summury.....                                                                                 | 38 |

|                                                  |    |
|--------------------------------------------------|----|
| Chapter 6 .....                                  | 38 |
| 6.1 Result.....                                  | 38 |
| 6.1.1 Optimization of initialization values..... | 38 |
| 6.1.1 Optimization of initialization values..... | 39 |
| 6.1.2 Optimization of initialization values..... | 39 |
| Chapter 7 .....                                  | 40 |
| 7.1 Conclusion .....                             | 40 |

## Chapter 1

### 1.1 Introduction

At present, population, energy and environmental problems are still major problems facing mankind. Among them, energy is an important material basis for promoting world economic development and the core driving force for improving people's living standards. Energy is a core issue concerning the fate of mankind. According to the BP Statistical Yearbook of World Energy in 2020 [1], carbon emissions from energy use increased by 0.5% in 2019, and China accounted for more than 75% of the net increase in global energy consumption. According to the World Energy Outlook 2019 report released by IEA in 2019 [2], China is now the top user of energy in the world, and experts predict that it will overtake the United States as the largest consumer of oil by the year 2040. And under the non-sustainable development strategy scenario, oil prices will continue to rise from 2018 to 2040 as global oil demand increases. The report also points out that global electricity demand will grow at an average annual rate of 2.1% through 2040, more than twice the rate of global energy growth, with industry (especially in China) being the main sector of power demand growth. With the rapid development of the global economy, human's demand for energy is expanding day by day, which leads to the shortage of some energy supplies and the continuous increase of prices. Environmental problems caused by carbon emissions and the waste of resources caused by improper use of energy are also becoming more and more serious. Therefore, energy conservation, emission reduction and green manufacturing are important measures we must take to address energy and environmental issues. The EIA classifies energy consumption by industry into residential, commercial, industrial and transportation sectors Sector). According to the statistics of Annual Energy Review released by the institution in 2019, the statistical values of four types of Energy consumption from 1949 to 2020 are shown in Figure 1.1 [6]. Figure 1 shows that

compared with other industries, industrial energy consumption has always been in the first place. In 2018, industrial energy consumption accounted for 32.45% of the total energy consumption and was still on the rise. The institute also proposed in Annual Nergy Outlook 2019 released in January 2019 that the global industrial energy consumption will continue to increase in the future, and it is estimated that the industrial energy consumption will increase by 50% in the next 30 years [7]. As a big manufacturing country, China's industrial energy consumption has been in a stable state. According to the data of China's Energy Statistical Yearbook released by China in 2020, China's total energy consumption in 1995 increased by more than three times compared with that in 1950, and China's industrial energy consumption accounted for more than half of the total energy consumption for a long time [8]. This shows that China's total energy consumption and industrial energy consumption also have a growing trend. However, China's industrial energy consumption accounts for more than half of the total energy consumption for a long time [8], which is much higher than the 32.45% reported by the United States [6], indicating that China's industrial energy consumption is high and energy efficiency is low, which also indicates that China has greater potential in reducing the waste of industrial energy consumption and improving the use efficiency of industrial energy consumption.

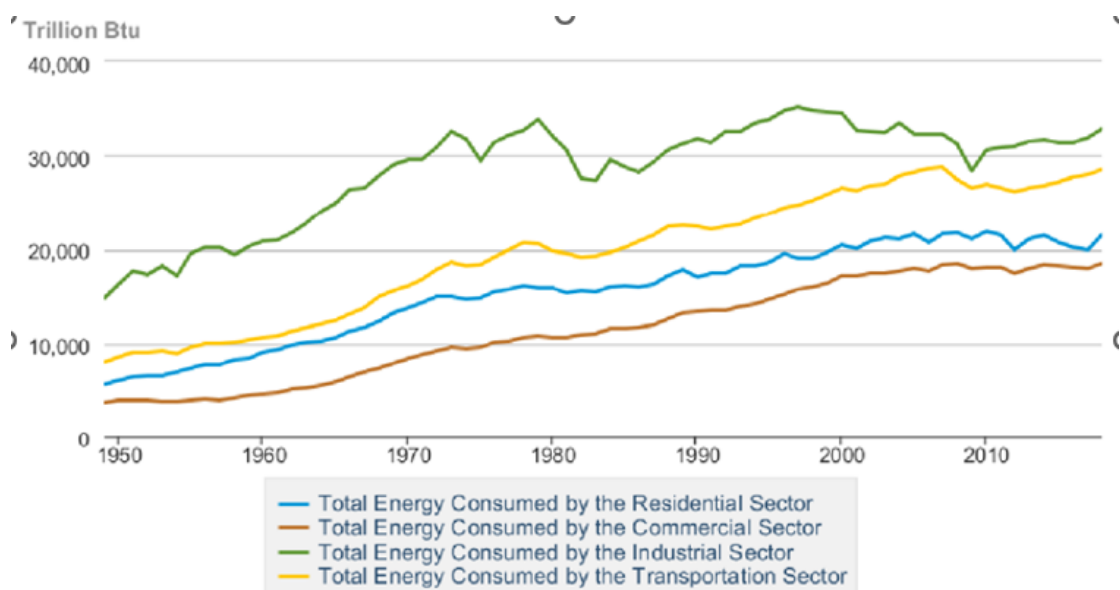


Figure 1 Energy consumption of the four industries in 1949 and 2020

Industry is the lifeblood of the national economy. In 2018, industrial energy consumption in China accounted for the largest proportion of total energy consumption in all industries, accounting for 66%[7], which is more than half of the remaining industries, as shown in Figure 1.1. As a large manufacturing industry, China's manufacturing industry accounts for 55% of the total energy consumption, and its

energy consumption has reached 83% in the industrial field, which is much higher than other industries. As the most important energy-consuming equipment in the manufacturing industry, machine tools have a large number, low energy efficiency and serious energy waste. In the five years from 2015 to 2019, the production of metal cutting machine tools in China has been reduced year by year, but in 2019, it still reached 421,000 units [8], the export volume of 9.431,800 units and the domestic possession of machine tools of 8 million units [9]. In addition, in 2017, the national electricity consumption was 6,482,097 million KWH, and the power loss in the manufacturing industry reached 52% [10]. Other studies have shown that the impact of electric energy consumption on the environment in the process of modern production and manufacturing accounts for about 99% of the impact of all energy sources on the environment [11]. As the main energy supply for CNC machine tool processing and production, the utilization rate of electric energy in CNC machine tool processing is lower than 30% on average [12]. With the increase of the number of machine tools, carbon dioxide emissions indirectly generated by power loss also increase, leading to further deterioration of the ecological environment [13].

Therefore, the study of energy consumption of CNC machine tools is not only conducive to reduce energy consumption, but also to promote ecological environmental protection and reduce greenhouse gas emissions. Among them, the numerical control machine tool processing energy consumption prediction, can provide a lot of data support for the machine tool energy consumption research, by improving the prediction accuracy to determine the optimal processing conditions, minimize the energy waste. Moreover, the prediction of processing energy consumption is also the key measure to promote the energy saving of NC machine tool processing process. According to the gap between the predicted value and the actual value, the abnormal situation in the processing process is found, and then the processing strategy is adjusted to promote the standardized use of energy to achieve the purpose of energy saving. At the same time, because there are many kinds of CNC machine tools, the power fluctuation in the processing process is also affected by many factors, including: machine tool system performance parameters, processing state, processing workpiece material properties, tool properties, process routes, processing parameters, etc. Moreover, the machining environment is complex and changeable, and the influencing factors of energy consumption are closely related, which increases the difficulty of energy consumption research. Through the research on the prediction method of processing energy consumption, the characteristics of machine tool energy consumption can be further understood, which is conducive to finding out the key influencing factors and improving the accuracy of energy consumption prediction. At the same time, it also lays a theoretical foundation for the energy-saving optimization of machining process, which is of great significance to promote green manufacturing.

Both the skyrocketing cost of power and the rising demand for manufactured goods are contributing to the rise in manufacturing energy costs, which have climbed by more than fifty percent since the late 1990s. Therefore, the optimization of machining process aiming at minimum energy consumption in CPDN is not only beneficial to the economic benefits of manufacturing enterprises, but also beneficial to improve their environmental performance. Machining process optimization involves machining parameters, tool selection, tool path design and other aspects. The results show that up to 6-40% energy saving can be achieved by optimizing the selection of machining parameters, cutting tools and tool path design. Therefore, it is imperative to reduce energy consumption by optimizing the processing parameters, and the energy consumption of the processing process should be taken as the optimization index to achieve this energy saving and consumption reduction. That is, the energy consumption prediction model is established to describe the relationship between energy consumption and processing parameters. Nonetheless, there is no credible estimate of energy usage in the machine tool literature. Establishing the prediction model is also challenging due to the nonlinear nature of the link between machining parameters and machining performance.

Soaring electricity prices and growing production demand are both increasing manufacturing energy costs, which have increased by more than half since the late 1990s. Therefore, the optimization of machining process aiming at minimum energy consumption is not only beneficial to the economic benefits of manufacturing enterprises, but also beneficial to improve their environmental performance. Machining optimization includes adjusting machining settings, choosing the right tool, and planning the best tool path.

In recent years, as a challenge, energy consumption in processing has attracted the attention of many researchers. At present, modeling methods can be divided into two categories: theoretical modeling method and empirical modeling method. The empirical modeling methods mainly include statistical regression modeling and artificial neural network modeling. In contrast to statistical regression modeling, modeling nonlinear complicated interactions using artificial neural networks is more amenable to their structure. On the other hand, it is not only influenced by factors like weights and thresholds, but also by inputs themselves.

## **1.2 Aims**

The project's overall goal is to identify and find a more excellent model can be solved, will go to used in the industrial manufacturing of machine learning so as to realize the energy saving of machine tool, not only in the numerical control machine tool processing energy consumption prediction model can provide a new algorithm, support for process parameters optimization method, and in such aspects as machine energy saving processing also has a broad application prospect

Due to the time constraints of the project, it was decided that it was not possible to achieve this overall goal. As a result, this project will concentrate on one important component, the development component of the algorithm model, and the following is the objective of this paper:

The establishment of a reliable prediction model of processing energy consumption can achieve a result of reducing use of available energy by adjusting parameters before processing. The genetic algorithm can optimize the initial weight, threshold, learning rate, and training rounds of BP neural network, so as to enhance the robustness of BP neural network. The data processed are the relationship between spindle speed, feed speed, cutting depth and cutting width and use of available energy in the process of machine tool processing. The BP neural network is optimized by genetic algorithm to iterate the optimal BP neural network parameters. The optimization characteristics of GA-BP neural network algorithm are verified. The prediction effect of traditional BP neural network is compared with the optimization effect of GA-BP neural network, and the optimization effect of GA-BP neural network after parameter optimization, and the rationality of this algorithm is verified.

### **1.3 Objectives**

Accurate and effective prediction of machine tool processing use of available energy has important reference and guiding significance for machine tool processing energy saving and emission reduction, process planning and so on. The main work of this paper is to analyze the research status of machine tool processing use of available energy, establish a prediction model of GA-BP ensemble algorithm based on data-driven and intelligent algorithm, and compare the prediction results of the model with the actual use of available energy values under different parameter Settings to confirm the prediction performance of the model. To achieve this goal, the following steps will be taken to achieve the completion of the project objectives:

For theoretical knowledge: briefly explain the research background and research significance related to the topic; Secondly, the topic source and research purpose of this paper are introduced. Then, the research status of use of available energy modeling and use of available energy prediction of CNC machine tools at home and abroad are analyzed and the existing problems are summarized

Analysis of factors affecting use of available energy of CNC machine tools: First, through the analysis of use of available energy of CNC machine tools, the factors affecting use of available energy of machine tools are preliminarily determined; Secondly, a data acquisition experiment platform was built, and experiments were designed according to the combination of theoretical analysis and experience to obtain use of available energy data. Then, the grey relation analysis method is introduced, and its theory and application steps are introduced. Finally, the use of

available energy data was substituted into the grey correlation analysis method to analyze the correlation between different influencing factors and use of available energy, and to screen out the main factors affecting machine tool processing use of available energy.

Use of available energy prediction model based on BP-GA ensemble algorithm: Firstly, the structure of artificial neural network is described. Secondly, combining the advantages and characteristics of BP neural network and GA algorithm, GA algorithm was used to improve the integration of BP neural network, and the prediction model of BP-GA ensemble optimization algorithm with stronger generalization ability was constructed. Finally, based on the experimental data, the feasibility of BP-GA integrated algorithm model in the application of NC machine tool machining use of available energy prediction is verified.

Case analysis of use of available energy prediction based on BP-GA ensemble Algorithm model: Firstly, Genetic Algorithm (GA) was introduced to optimize and improve the BP neural network, and the use of available energy prediction model of BP-GA Algorithm was constructed. Secondly, the use of available energy prediction model of BP-GA algorithm is verified on the basis of data driven. Finally, by comparing the prediction results of the non-optimized BP-GA algorithm, the optimized BP-GA algorithm, the traditional BP algorithm and three use of available energy prediction models, the prediction accuracy of the NC machine tool processing use of available energy prediction model based on the BP-GA ensemble algorithm is evaluated.

## **Chapter 2**

### **2.1 Literature Review**

In this paper, the energy consumption of CNC machine tools is designed, and the role of related machine learning algorithms in energy consumption prediction. In dealing with the problem of machine tool energy consumption is crucial. In order to better understand the content of the project and follow up the progress of the project more efficiently, the literature review at home and abroad is summarized from two parts: the research status of use of available energy of CNC machine tool processing system and the research status of use of available energy prediction methods of CNC machine tool processing system. The research status of use of available energy of CNC machine tool processing system includes two sub-parts: use of available energy of equipment layer and use of available energy of process layer; The use of available energy prediction method of NC machine tool processing system includes three sub-parts: traditional theoretical use of available energy prediction and optimization, traditional experimental fitting use of available energy prediction and optimization,

and machine learning-based data-driven use of available energy prediction and optimization.

## **2.1 Research status of energy consumption of CNC machine tool processing system**

In terms of energy efficiency research of manufacturing systems, a lot of achievements have been made in energy efficiency research of process manufacturing industry, while energy efficiency research of discrete manufacturing industry started relatively late. Studies in recent years have found that discrete manufacturing industry has huge space for energy saving and consumption reduction [21-22], and its energy consumption research has been widely concerned by scholars and experts at home and abroad. As a typical discrete manufacturing system, the energy consumption problem of CNC grinding machine processing system is a current research hotspot, which is mainly developed from two levels of energy consumption of equipment layer and work layer, which is explained successively in the following.

### **2.1.1 The power consumption at the Device layer is abnormal**

Use of available energy is closely related to multiple components of CNC machine tools and involves many influencing factors. Therefore, many experts and scholars at home and abroad have carried out research on use of available energy of machine tools and equipment layer and achieved many achievements. Professor GUTOWSKI's team at MIT et al. [14,22-27] conducted in-depth and detailed research on the use of available energy of manufacturing systems, and used a large number of machine tool cutting experiments to test and analyze the use of available energy under different operating states. DAHMUS[23] incorporated environmental factors into the analysis of machine tool use of available energy, analyzed the use of available energy of machining processes under different working conditions, measured the use of available energy of 36 processing processes of 10 typical manufacturing processes, and proposed a method for measuring the environmental load of manufacturing processes. Figure 1.4 shows the use of available energy composition of a 6kW machining center at work. It can be seen from the figure that the startup use of available energy and operation use of available energy can be approximated as constants, while the use of available energy in the processing process is not a static constant, but changes dynamically with the change of the working state. Based on the above experiments and analysis, GUTOWSKI divided the use of available energy of machine tools into fixed use of available energy and variable use of available energy. Variable use of available energy did not account for a high proportion of the entire use of available energy of machine tools, and most of the use of available energy of machine tools was fixed use of available energy [24].

Kordonowy et al. [27] fitted machine tool fixed use of available energy model and variable use of available energy model based on previous research and combined with the influence of material removal rate on use of available energy, and further verified the accuracy of machine tool variable use of available energy model through different load experiments. From the perspective of the integrity of CNC machine tools, the Dornfeld team at the University of California, Berkeley, USA and the Verl team at the University of Stuttgart, Germany have carried out a lot of detailed research. Professor Dornfeld's team combined a large number of basic and experimental data to fit a vertical milling machine power analysis model [28-29]. In this model, the power of vertical milling machine is analyzed by taking the workpiece feed, spindle speed, cutting speed and other process parameters as variables. Based on the analysis of the impact of process parameters on machine tool use of available energy, the impact of tool path on use of available energy is further discussed, and the use of available energy evaluation system is developed to analyze and evaluate it [30]. Professor Verl's team [31-32] divided the machining process of CNC machine tools into four different stages: start-up stage, no-load stage, machining stage and shutdown stage, and carried out systematic theoretical research and a large number of experimental studies on the energy characteristics of the four stages. Based on the above research, Verl constructs the economic index of machine tools, namely the ratio of output benefit to total input, which can be used as an important index to measure the energy efficiency of machine tools.

### **2.1.2 Study on use of available energy of process layer**

According to the input process information, the CNC system of the machine tool controls the movement of the machine tool to remove the excess material of the workpiece and process the workpiece into finished products according to the requirements. The process information elements involved in the use of available energy research of process layer mainly refer to the information of process route and process parameters. Different process information leads to different use of available energy of machine tools. Even if the same processing system processes the same workpiece, the processing process route is different, or the adjustment of the processing process parameters, it will also lead to the detailed differences in system use of available energy. On the basis of analyzing the test data, Romani DRAGANESCU et al. [33] established a power consumption model based on basic process parameters by using the response surface method, and proved the nonlinear influence of process parameters such as cutting force, cutting depth, speed and material removal rate on power consumption by taking the vertical grinding machine tool as a processing case. Dietmair et al. [34] analyzed the use of available energy characteristics of each energy consuming component of NC machine tool under different processing conditions from the perspective of energy consuming

components, and analyzed the use of available energy characteristics of NC machine tool under each running state in the processing process, and constructed an use of available energy model for each running state of NC machine tool based on multi-source energy consuming components. Literature [35]

Under the premise of considering the life of the tool, the area composed of the parameters such as the back bite, feed rate and feed speed is taken as the search space, and the optimal combination of machining parameters is searched to match a certain processing technology in the machining process of the parts, so as to minimize the processing use of available energy. NARITA et al. [36] from Japan proposed an environmental impact model equivalent to CO<sub>2</sub> emission in the process of machine tool processing, which took the machine tool use of available energy, tool state, quantity of coolant, quantity of lubricating oil and amount of metal chip as variables. According to the orthogonal test of three milling methods and four parameters in literature [37], the material removal rate can make the power consumption vary in a wide range of 5%~333%. The experiment shows that optimizing the processing parameters can effectively reduce the use of available energy of the system. Gutowski[38] used the thermodynamic analysis method to establish the energy model of the manufacturing system based on different technological processes, and used specific cases to analyze the impact of workpiece material on the use of available energy of the system. The use of available energy is not only related to the process route, but also closely related to the process parameters. Herrmann et al. [39-40] set the processing parameters under different processing conditions and explored the use of available energy rule of NC machine tools by measuring the use of available energy under different processing conditions. Literature [41] summarizes the research status of NC machine tool machining parameters, and points out the existing problems and new research directions of NC machine tool machining parameter optimization. Professor Liu Fei [18] divided the use of available energy of mechanical machining system into three parts: no-load use of available energy, cutting use of available energy and additional use of available energy (which depend on the processing conditions and the amount of material removal), while literature [42] analyzed the use of available energy of CNC machine tools in cutting process from two aspects: load-independent use of available energy and load-dependent use of available energy. A prediction model of cutting use of available energy of NC machine tools based on support vector machine was constructed. Ghosh et al. [43] took high-speed deep grinding process as the research object, established an use of available energy analysis model through mechanical analysis of grinding process, and found out the main use of available energy links of grinding process. In the process of machine tool processing, the energy consumed by the materials directly used for cutting is the effective use of available energy of machine tool. For the analysis of different processing parameters on the use of available energy of the numerical

control surface grinding machine, the processing quality and the comprehensive effect of the indicators such as noise, deng from zhaohui, etc. [44] using the Euclidean distance method and the grey correlation method of related process parameters are analyzed, and the results show that feed speed, the most profound effect on the grinding use of available energy of grinding depth second, the least is the linear velocity of grinding wheel. Literature [45] has made a detailed analysis of the factors affecting the use of available energy of machine tools in the cutting process, and concluded that the main factors affecting the use of available energy include: cutting process parameters, tool material and geometric parameters, tool wear state, workpiece material attributes, machining environment and conditions, etc. Cuppini et al. [46] fitted the linear relationship between cutting use of available energy and tool wear through a large number of experimental data. Literature [47] points out that the cutting use of available energy of machine tools is mainly affected by tool materials, tool geometric parameters, workpiece materials and cutting fluid through geometric models. Yoon et al. [48] pointed out that the milling use of available energy increases with the severity of tool wear, and the proportion of the total use of available energy of the machine tool will also increase significantly, which was verified by experiments. The change of milling power depends directly on the process parameters, while the increase of milling power with the increase of tool wear severity depends on the process conditions. Yan et al. [49] adopted the grey correlation method to establish a multi-objective optimization model and solve the optimal process combination by taking the use of available energy, processing quality and processing efficiency in the milling process as the optimization objectives. By introducing use of available energy into CNC machining process, Newman et al. [50] proved that there is an influence relationship between process parameters and energy efficiency. Zhang et al. [51] proposed a multi-step dry milling process parameter optimization method, which took high efficiency, low consumption and low carbon as the optimization goal, and deeply studied the influence relationship among machining time, use of available energy, carbon emission and cutting process parameters of CNC machine tools. The above research provides support for the establishment of the use of available energy model of CNC grinding machine processing system in this paper, but the correlation between use of available energy and process information is not deeply analyzed.

## **2.2 Use of available energy prediction method of CNC machine tool machining system**

At present, with the enhancement of people's awareness of environmental protection, the use of available energy prediction and optimization of CNC machine tool processing has become a hot issue in the academic community, and has been widely concerned by the academic community at home and abroad. Focusing on the main

issues of this project, the following three aspects of traditional theoretical use of available energy modeling, traditional experimental fitting use of available energy modeling and data-driven use of available energy modeling will be reviewed.

### **2.2.1 Traditional theoretical use of available energy prediction and optimization**

Most of the traditional use of available energy models are established by theoretical or experimental methods. Based on the structure of the machine tool, some researchers have analyzed the use of available energy characteristics of each subsystem of the machine tool through theoretical modeling, so as to establish the use of available energy model of the machine tool, and use the established model to optimize. Such as YanWei subsystem unit of nc machine tools can be divided into time-varying unit and time invariant use of available energy unit use of available energy, and respectively to different use of available energy unit theory analysis under the different running state of machine tool, therefore the nc machine tool use of available energy model is set up, and put forward the nc machining system based on niche genetic algorithm efficient multi-objective optimization algorithm [18]. Jia et al. used the method of motion-element analysis to analyze the motion-element composition of machine tools during the cutting period, and obtained the use of available energy function of each motion-element through theoretical analysis to construct the use of available energy prediction model of CNC machine tools, which was applied in the outer circle turning [19]. Li and Kara divided the use of available energy of the machining process into the use of available energy of the cutting part and the use of available energy of the non-cutting part. The use of available energy of the cutting part was calculated by the cutting force, and the use of available energy of the non-cutting part was calculated by the friction force, so as to build the theoretical use of available energy model of the machine tool and optimize the use of available energy in the CNC turning process [20]. Zhong et al. established a specific use of available energy model including spindle speed, cutting speed, feed speed and cutting depth, proposed a decision rule to select the optimal cutting parameters to achieve the minimum use of available energy, and applied the decision rule in rough outer circle turning experiment [21]. Li Congbo et al. analyzed the use of available energy composition of CNC milling machine tools, divided the machining process into different periods, obtained the use of available energy composition of machine tools in different periods, established the use of available energy prediction model, used cutting experiments to fit the coefficients of the theoretical model, and used continuous tabu search algorithm to optimize and solve the model [22]. From the perspective of energy transfer, Liu et al. analyzed the correlation between cutting power and power loss of each part of the spindle system, and finally proposed a method to obtain real-time energy efficiency without cutting force measurement instrument, but only with the input power of the machine tool and the spindle speed

[23]. Guo et al. analyzed the correlation between machine power and process parameters, established a finishing machining use of available energy model considering cutting speed, back bite and feed speed, and proposed an optimization method of finishing turning cutting parameters taking into account use of available energy and surface roughness [24]. Lv, etc on the basis of the spindle motor control principle, including the moment of inertia calculation of spindle drive system, analyzes the spindle power and power spindle to overcome inertia force, thus established the numerical control lathe spindle acceleration use of available energy model, and based on this, advances the thinking of spindle of the nc machine tool use of available energy prediction of acceleration and deceleration and optimization research [25]. Wang Qiulian et al. divided the multi-energy source system of CNC machine tools into four categories: processing power, processing associative auxiliary, power associative auxiliary and other systems, analyzed the energy flow under various systems, and obtained the correlation relationship between each energy flow [26]. According to the use of available energy characteristics of NC machine tools, Deng et al. divided the use of available energy of NC machine tools into basic use of available energy, use of available energy of feed system, use of available energy of spindle system and use of available energy of auxiliary system, and established the minimum cutting ratio use of available energy and minimum processing time.

### **2.2.2 Traditional experimental fitting use of available energy prediction and optimization**

In view of the traditional theoretical modeling is difficult to use theoretical formulas to comprehensively analyze the use of available energy of each part of the machine tool, some researchers regard the machine tool modeling as a black box problem, and directly obtain the mapping relationship between the use of available energy and parameters of the machine tool by means of experimental fitting. For example, Kant et al. established a multi-objective prediction and optimization model of use of available energy and surface roughness with process parameters as variables by combining grey correlation with principal component analysis and response surface method. The results show that the cutting feed is the most influential machining parameter, followed by cutting depth and cutting speed [28]. Park et al. considered factors such as cutting speed, feed speed, radius of tool tip arc, rake Angle and rake Angle, and used mixed regression and response surface method to present the relationship between machining parameters and specific required cutting energy and energy efficiency, and established a quadratic mathematical model of energy efficiency [29]. Through cutting experiments, Li et al., based on Taguchi method and response method, fitted the regression function of machine tool energy efficiency using spindle speed, feed speed, back cutting capacity and side cutting capacity, and used multi-objective particle swarm optimization algorithm to find a set of balance

parameters between lower processing time and higher energy efficiency [30]. Oda et al. improved the cutting conditions of five-axis machine tools according to tool Angle and cutting speed to reduce use of available energy, determined the optimal tilt Angle and cutting speed to reduce the use of available energy of machine tools through cutting tests, and compared the workpiece produced under standard and improved cutting conditions to verify the effect of reducing use of available energy [31]. Kumar cutting fluid was studied, such as nozzle radius, such as cutting speed, feed rate and cutting depth input parameters and their interaction on the power factor, active power, energy efficiency, the effect of surface roughness and material removal rate, using taguchi experimental design, by using the combined method of analytic hierarchy process (ahp) and entropy weight method in the weights for each indicator to distribution, The multi-performance composite index was obtained [32]. Arriaza et al. considered the influence of spindle speed, feed speed, cutting depth and cutting width on machine tool use of available energy, and used response surface method and expectation function method to obtain the correlation between various influencing factors, and finally concluded that spindle speed has the greatest impact on use of available energy and cutting width has the greatest impact on time [33]. Bilga et al. carried out experimental analysis on CNC rough machining, studied the influence of important factor variables such as process parameters and tool parameters and their interaction on these use of available energy, conducted experimental design by Taguchi orthogonal experiment, and optimized the energy efficiency, active power and power factor [34]. Zhang with feed speed and spindle speed and quantity of the turning factors for the design of orthogonal test, analysis in dry cutting, minimal quantities of lubricant and wet cutting processing, various process parameters on the numerical control turning processing can than, roughness, and the influence of cutting force, and put forward the workpiece surface quality is high, the machining principle of the optimal process parameters of high efficiency, low use of available energy, [35]. Wang et al. divided cutting use of available energy into plastic deformation energy in the main deformation area, friction work and flow between the cutter head interface.

### **2.2.3 Data-driven use of available energy prediction and optimization based on machine learning**

The data-driven approach is to reveal the operating mechanism of the system by analyzing the correlation between data, which can cope with large-scale complex systems and has powerful analysis and decision-making capabilities [38]. With the development of sensors, industrial Internet, big data and other technologies, machining process data collection and analysis and machine learning algorithms have been widely used. There are many algorithms of machine learning, among which the more common ones are artificial neural network [39], support vector machine [40], etc. Data-driven use of available energy prediction methods using machine learning

are also gradually emerging, and preliminary research results have been achieved. Such as Xiao firstly analyses the use of available energy of cutting time, on the basis of clear the influence factors of the use of available energy of cutting time, and then analysis these factors data, the numerical control turning processing process using neural network method to establish the thinking of cutting speed, feed rate and back turning turning process use of available energy prediction model, and carries on the optimized [41]. Lv Jingxiang et al. used sample classification and RReliefF algorithm to analyze the influencing factors of use of available energy, and then used data-driven method to predict the use of available energy of turning and drilling, and compared the prediction effects of three algorithms, including neural network, support vector regression and random forest [42]. Bhinge et al. took process parameters as variables, and used Gaussian process to predict the use of available energy of different process characteristics such as milling surface and slot in CNC milling. They pointed out that Gaussian process regression algorithm had superior performance in predicting machine tool use of available energy, and finally optimized tool routing with use of available energy as the objective [43]. According to the specific milling process, Zhang et al., taking cutting speed, feed rate and cut size as variables, established the use of available energy model of milling processing at different time periods through sliding filtering, multiple linear regression and improved gene expression programming method [44]. Senthilkumaar et al. combined genetic algorithm with artificial neural network to build a prediction model of tool wear and surface roughness with machining parameters such as cutting speed, feed rate and back bite as variables [45]. Abele et al. used artificial neural network algorithm to construct use of available energy models related to feed speed, spindle speed, coolant lubricating oil quantity and switching state of peripheral equipment for experimental simulation, real-time monitoring of the energy demand of machine tools and their components, and predicting their future energy behavior [46]. Quintana et al. collected the use of available energy data of the spindle and X, Y and Z feed axes in the milling process, and used the collected data to establish the use of available energy model of the milling process using artificial neural network algorithm, and analyzed the influence of spindle speed, feed per tooth, side feed, back feed and tool tip radius on the processing use of available energy [47]. When Nguyen determined the roughness characteristics as the constraint condition, he used Kriging interpolation method to establish the models of cutting depth, spindle speed, feed speed, tool tip radius and cutting specific energy, and used archive-based microgenetic algorithm to obtain the optimal processing parameters [48]. All the above is only for a particular action or in a specific machining process under the condition of static use of available energy model is set up, but in the process of machining processing conditions are often complex, in the event of change in the

processing conditions, the above method to adjust and amend the model very hard, can't well meet the need of dynamic mechanical processing.

## **Chapter 3**

### **3.1 Methodology**

According to the previous research, the use of available energy of CNC machine tools is complex. If a model is established for each processing period, it is necessary to analyze the use of available energy mechanism and know the specific value of each parameter. But if the problem of process use of available energy of machine tool as a black box, with the method of neural network, only need to know the use of available energy under the different processing methods of machine tools, can avoid to use of available energy analysis and modeling of the processing time, but also access to use of available energy and the processing mode function mapping relationship between different parameters. , therefore, need to set up the parameters as the main variable model to forecast processing and total use of available energy, the use of available energy of this chapter USES the advantages of integration algorithm, GA algorithm integrated to optimize the BP neural network is adopted to establish the new model, and applied to the numerical control machine tool processing use of available energy prediction study, fill the blank of the part of the nc machine tool use of available energy prediction research

### **3.2 GA algorithm**

Genetic algorithms simulate the natural law of survival of the fittest by natural selection. It usually uses biological heuristic operators to carry out an optimization, such as selection, crossover and mutation, to generate high-quality optimization and get a better solution to the search problem. In this way, after the evolution of a given number of generations, it is very possible to obtain individuals with high fitness function value through selection, crossover and mutation. Genetic algorithm is essentially a search algorithm, and has its basic essential characteristics like most search algorithms. This section will detail the idea of genetic algorithm, steps and specific methods of implementation.

#### **3.2.1 GA algorithm theory**

Genetic algorithms simulate the natural law of survival of the fittest by natural selection. It usually uses biological heuristic operators to carry out an optimization, such as selection, crossover and mutation, to generate high-quality optimization and get a better solution to the search problem. Using the notion of biological evolution as its guiding principle, the genetic algorithm transforms the issue at hand into a process analogous to that of biological evolution. It then develops the next generation

by means of selection, crossover, mutation, and other processes, so as to save the individuals with high fitness value as much as possible. In this way, after the evolution of a given number of generations, it is very possible to obtain individuals with high fitness function value through selection, crossover and mutation. Genetic algorithm is essentially a search algorithm, and has its basic essential characteristics like most search algorithms. This section will detail the idea of genetic algorithm, steps and specific methods of implementation

Genetic algorithm (GA) is a search algorithm which combines the theory of evolution and genetics. It is a kind of based on the survival of the fittest of highly parallel, random and adaptive optimization algorithm, through a series of operation such as selection, crossover and mutation will question solution in the form of a chromosome group performance, through generations of evolution, finally find out individual fitness value maximum, and that this individual is corresponds to the optimal solution of the problem.

- Chromosomes: Chromosomes are sometimes referred to as gene individuals, which is another name for chromosomes. Individuals make up a population, which is made up of a given number of people. The size of a population may also be referred to as the number of persons that make up that population.
- Gene: represents the characteristics of an individual. For example, if an individual is the hundred digit 105, then "1", "0" and "5" are the genes of the individual.
- Loci: An Algorithm that represents a specific location of a gene on a segment of another gene. This location is called a Loci.
- Fitness value: represents the degree of adaptation of each individual to the environment. In order to reflect the individual's adaptive ability, the function used to calculate the fitness value of each individual is called the fitness function.

### **3.2.1 GA algorithm step**

The basic operation process of genetic algorithm is as follows:

1. Initialization: randomly generate N individuals as the initial group, and define the number of iteration layers.
2. Individual evaluation: Calculate the fitness value of each individual in the group.
3. Selection: Apply the selection operator to the group. The purpose of selection is to pass on superior individuals to the next generation with high probability or to add new individuals to the population of the next generation by pairing with other individuals.
4. Crossover: the crossover operator is applied to the population. The selected individuals are crossed to produce new individuals.

5. Mutation: apply mutation operator to the population. When the individual meets the conditions of mutation, a random mutation of its gene will produce a new individual.

6. Iteration termination: When the number of iteration layers is met, the optimal individual obtained in the evolution process is taken as the optimal solution of the problem.

The flow chart is as follows:

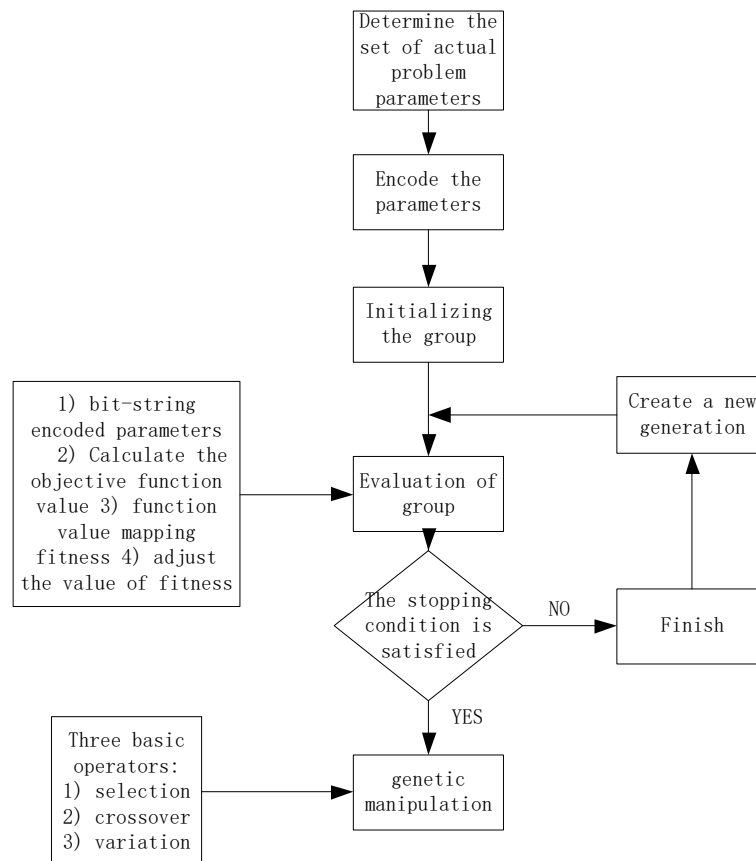


Figure 2 Flowchart of genetic algorithm

The crossover operation of a genetic algorithm is the process by which two paired chromosomes swap a certain portion of their genes to create two new people. The crossover operators single-point crossover, two-point crossover, multi-point crossover, uniform crossover, and arithmetic crossover are all applicable to people with binary genotypes. In the following, we take multi-point crossover as an example to illustrate its crossover results. For example, the 12-bit binary number shown below is the genotype of an individual and two individuals are demonstrated:

101011110000

101011110000

After a multi-point crossing, the five to eight bits of both sides switch places, and the result is as follows:

101000001111

101011110000

The practice of selecting good individuals from a group and eliminating fitness individuals is called selection. The purpose of selection is to preserve the excellent, the poor or the performance of the average level of elimination. In order to ensure that the genetic algorithm follows the law of nature in the selection operation, that is, those with higher fitness value may be screened out, and those with lower fitness value may be selected for the next generation. In this experiment, the betting wheel algorithm which is frequently used in the selection operator of genetic algorithm is adopted. Here, the betting wheel algorithm is also taken as an example to illustrate the selection process.

Gambling wheel algorithm: After the evaluation of all the individuals in the population by the genetic algorithm, the fitness value of each individual is obtained and the total fitness value is calculated. Suppose that there are five individuals and the fitness values of the five individuals are 5, 8, 7, and 2, then the total fitness is 25. Then in the selection process, the odds of these five individuals being selected are:

A1 is equal to  $(5/25)$  times 100% is equal to 20%

$A2 = (8/25) * 100\% = 32\%$

$A3 = (7/25) * 100\% = 28\%$

$A4 = (2/25)$  times 100%=8%

$A5 = (3/25)$  times 100%=12%

The odds of these five individuals passing the wheel algorithm are shown below:

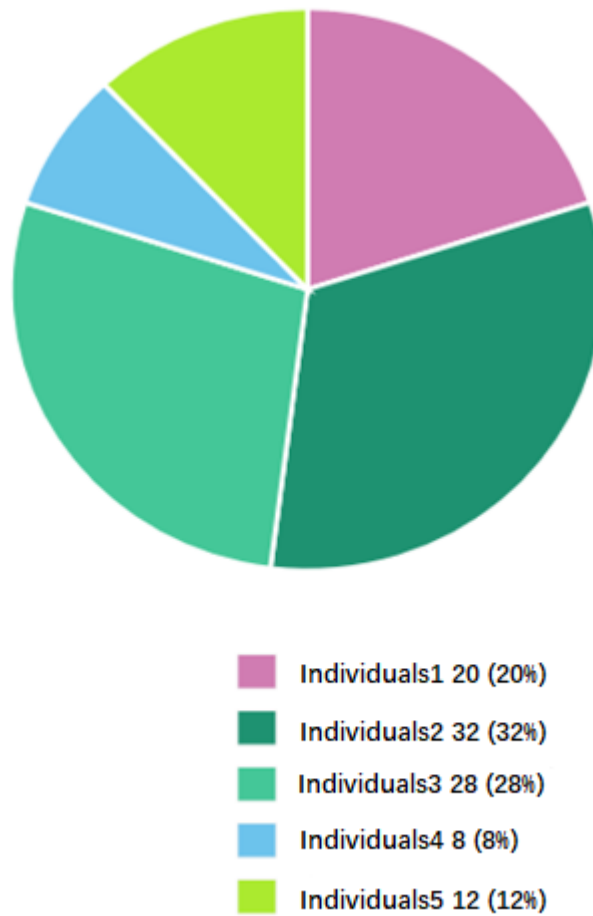


Figure 3 Wheel betting algorithm

In the context of the genetic algorithm, the term "mutation operation" refers to the process of replacing some genes in the coding string of an individual chromosome with other genes., which must be random and the probability of occurrence is very small, so as to form a new individual. For example,

101011110000

The result of the mutation is

101011010000

In the 1990s, genetic algorithm reappeared in the eyes of researchers, both in theory and application have attracted a large number of researchers into the experiment. In the research field, the application research is more favored by the researchers. The genetic algorithm's capabilities in terms of both path optimization and rule learning have seen substantial improvements, in addition to the expansion of the application field.. At the same time, the industrial application research is also expanding. In recent years, some new theories and methods have been put forward by researchers and applied to industrial production, which have injected new vitality into genetic

algorithms. Along with the expansion of application fields, in the research of genetic algorithm has some new ideas, which is more attract the computer industry is based on the genetic algorithm of machine learning, a new research direction in the searching space of genetic algorithm from the relatively discrete before optimization search algorithm is promoted to a new machine learning algorithm of dynamic.

### **3.3 BP neural network algorithm**

The BP neural network was invented by scientists over the last few decades and it's still here. BP neural network is a kind of multi-layer feedforward neural network which propagates backward according to the error. It is the most widely used neural network. Artificial neural network is a neural network that simulates human brain by computer. It is composed of several simple units combined in parallel. This organization can simulate the reaction of neural units of biological brain to external things. The neuron model is one of the key models, which is designed to simulate the human brain. The basic idea of back propagation in BP neural network is to adjust the network parameters by calculating the error between the output layer and the given value. The final desire is to make the error of the model smaller and smaller

#### **3.3.1 BP neural network algorithm theory**

BP neural network consists of three parts: input layer, hidden layer and output layer. In the training process, it is not necessary to give the functional relationship between input and output in advance, and it can self-train according to the given data set to learn a certain rule. The basic idea of BP neural network is the gradient descent method, which is used to continuously optimize the weight matrix and other parameters to get the model with the minimum error between the output value and the expected value. BP neural network transmission of signal transmission has forward and reverse transmission, calculation error in the forward propagation, the layers of error propagation to the last layer, if the actual value and the predicted values have stepped into the stage of back propagation error, with back propagation to modify weight matrix, the offset value, the parameters such as the training model of low loss function. When a better model can be obtained after repeated training, the model trained by BP neural network can process the input information similar to the training dataset for researchers.

Its topology is as follows:

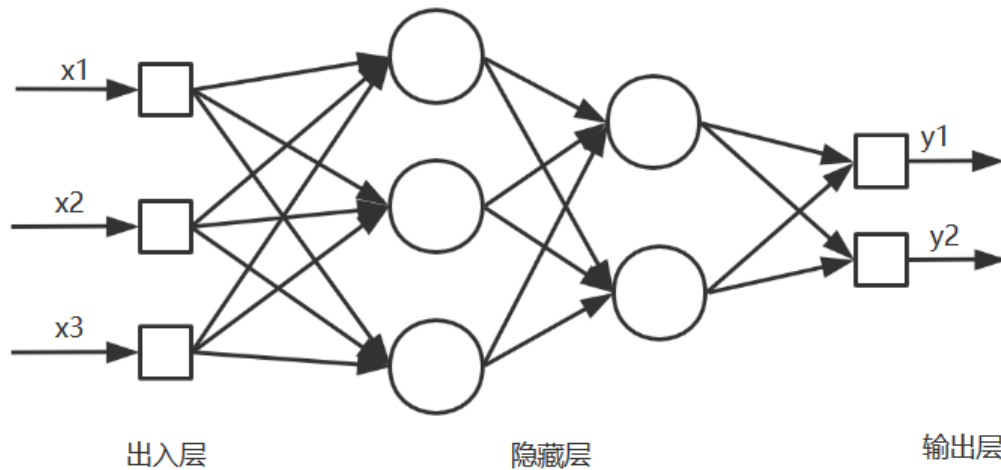


Figure 4 Topology diagram of BP neural network

### 3.3.2 BP neural network algorithm step

In the execution of BP neural network, it can be roughly divided into seven steps. Step 1: Set the number of nodes in the input layer, hidden layer and output layer, initialize the weight matrix and offset, and determine the incentive function given the learning rate and the number of training rounds. Step 2: After receiving the data from the input layer, the hidden layer forwards the results obtained through its own parameters and relations to the output layer. Step 3: Output layer Compare the output result of this layer with the actual value and calculate the error. Step 4: Update the weight and bias through back propagation, and achieve a purpose of reducing the loss function value through gradient descent method. Step 5: Judge whether the number of training layers is reached. If the number of training rounds is reached, the training will end; if the number of training rounds is not reached, the second step will be continued. Through the above five steps, it can be concluded that an optimal solution corresponds to an optimal model. This model is then the optimal model that fits the input data. Feeding similar data into the model yields output data that meets the expectations of that input data.

Gradient descent: The popular understanding of gradient descent is the process of a person going down a mountain. Go down from the top of the mountain, in the process of constantly going down, pause several times to check their distance from the beginning position and the distance from the last position, in order to reach the bottom of the mountain, that is, the lowest point of the function value. The simple gradient descent method is divided into five steps. Step 1: Check your current location. Step 2: Take your current position as your starting point and look for a path that will fall fastest. Step 3: Follow the path specified in step 2 and take a small step down the path. When you complete the small step, the current position must be lower than the

previous position. The magnitude of this small step can be adjusted by itself. Step 4: Go back to Step 1. Step 5: Terminate the algorithm at the minimum possible. Training object, of course, and often is not a simple 2 d graphics, a lot of training object is similar to many of 3 d image of high and low different hills, when the gradient descent method for training on a hill, if reached the bottom of the hill, gradient descent rule think they obtain the minimum, but this is not a global optimal solution, This minimum is only the minimum for that hill and not the global minimum. Therefore, in BP neural network, the initialization of weights and biases is often random, and the purpose is to carry out the process of gradient descent globally. Different local optimal solutions are obtained by randomly initializing parameter values for many times, and then the optimal solution is selected from these local optimal solutions. However, in the experiment, the gradient descent method often falls into the local optimal solution and cannot get out of the local optimal solution because the learning rate is too large or too small, and the weight and bias randomly generated are not good.

Although BP neural network has the general advantages of neural network, it is not perfect. The weight and bias of the network are locally optimized through gradient descent, which is easy to fall into the local optimal solution, and different initialization values have a great impact on the training. In addition, the structure of BP neural network is not unified, there is no clear definition rule, too large structure is prone to overfitting, too small structure may not converge, generally can only be selected by experience. If only the gradient descent method is used to approximate the optimal value, the BP neural network will often fall into the local optimal solution. To sum up, simple BP neural networks have been unable to satisfy researchers to solve complex problems.

## **Chapter 4**

### **4.1 Data collection**

This paper uses HIOKI3390 power analyzer and CNC machine tool to build power data acquisition device, in the machine tool electrical control cabinet through voltage clamp and current sensor connection 3390 power analyzer, and the analyzer data copy to the computer, the computer end to achieve the analysis and processing of power analyzer data. Among them, the power analyzer measures the voltage and current of the three-phase power supply of the CNC machine tool through the voltage clamp and the current transformer respectively, and obtains the power data of the machine tool. The experimental site is shown in Figure 2.3.



Figure 5 Field diagram of the experiment

Due to the limitation of the project time period, the experiment was carried out for one month according to the analysis of the use of available energy composition of CNC machine tool processing. In addition to time parameters, the use of available energy is related to standby power, machine tool no-load power, auxiliary process power and material cutting power. The internal factors involved include inherent machine tool properties, spindle speed, tool properties, material properties, cutting parameters. When the machine tool is specified, the factors to be considered include: machine tool no-load power, spindle speed, tool properties, material properties, cutting parameters, without considering the auxiliary function system work. The supplement of some experimental data comes from literature [50] using gray correlation analysis method to process experimental data, and obtain four important indicators affecting machine tool processing use of available energy: Spindle speed, Feed speed, Cutting depth and cutting width, the corresponding data set of this experiment is obtained by screening these four indicators:

| n(r/min) | f(mm/min) | ap(mm) | ae(mm) | EC(KJ)  |
|----------|-----------|--------|--------|---------|
| 1000     | 200       | 0.2    | 5      | 555.802 |
| 1000     | 200       | 0.3    | 10     | 204.929 |
| 1000     | 200       | 0.4    | 15     | 108.519 |
| 1000     | 250       | 0.2    | 5      | 446.109 |
| 1000     | 250       | 0.3    | 10     | 166.050 |
| 1000     | 250       | 0.4    | 15     | 89.823  |
| 1000     | 300       | 0.2    | 5      | 381.832 |
| 1000     | 300       | 0.3    | 10     | 142.976 |
| 1000     | 300       | 0.4    | 15     | 73.988  |
| 1500     | 200       | 0.2    | 5      | 357.042 |
| 1500     | 200       | 0.3    | 10     | 162.727 |
| 1500     | 200       | 0.4    | 15     | 319.031 |
| 1500     | 250       | 0.2    | 5      | 289.604 |
| 1500     | 250       | 0.3    | 10     | 133.648 |
| 1500     | 250       | 0.4    | 15     | 258.476 |
| 1500     | 300       | 0.2    | 5      | 233.559 |
| 1500     | 300       | 0.3    | 10     | 112.551 |
| 1500     | 300       | 0.4    | 15     | 213.109 |
| 2000     | 200       | 0.2    | 5      | 264.303 |
| 2000     | 200       | 0.3    | 10     | 445.797 |
| 2000     | 200       | 0.4    | 15     | 185.620 |
| 2000     | 250       | 0.2    | 5      | 213.939 |
| 2000     | 250       | 0.3    | 10     | 358.579 |
| 2000     | 250       | 0.4    | 15     | 151.343 |
| 2000     | 300       | 0.2    | 5      | 180.886 |
| 2000     | 300       | 0.3    | 10     | 306.850 |
| 2000     | 300       | 0.4    | 15     | 128.147 |

Grey correlation analysis is a statistical method to analyze the correlation degree between multiple factors [53]. The core idea is to determine whether the relationship between the index and each influencing factor is close by the degree of similarity between the curve. Through the quantitative analysis of the system dynamic process development, the method compares the geometric relationship of sequence data, so as to get the difference and correlation degree between indicators and influencing factors. In addition, the gray theory involved in the gray correlation analysis has a small demand for the number of samples and is not affected by the distribution law of samples [50], so the calculation amount is small and it has advantages in the correlation analysis.

Therefore, grey correlation analysis is very suitable for studying the relationship between machine tool use of available energy and influencing factors. The method of sample data set is no special request, from the perspective of fuzzy analysis of

machine tool use of available energy influencing factors and processing, the connection between the use of available energy in machine tool use of available energy influencing factors and processing use of available energy curve geometric similar measure its correlation degree, can better describe the factors affecting use of available energy and process the nonlinear relationship between the use of available energy. Based on this, the grey correlation analysis method is used to determine the main factors affecting the use of available energy of CNC machine tools, which lays a foundation for the establishment of use of available energy prediction model.

#### (1) Determine the reference sequence and comparison sequence

The data series reflecting the behavioral characteristics of the system are used as the reference series, and the data series affecting the behavioral characteristics of the system are used as the comparison series. According to the sample data and characteristics of machine tool use of available energy, the sequence of use of available energy value is used as the reference sequence, and the sequence of other influencing factors is used as the comparison sequence. The reference sequence is expressed as:

$$z_0 = \{z_0(1), z_0(2), \dots, z_0(k)\} \quad (k = 1, 2, \dots, m)$$

The comparison sequence is expressed as:

$$z_i = \{z_i(1), z_i(2), \dots, z_i(k)\} \quad (i = 1, 2, \dots, n)$$

Where,  $z_0(k)$  -- the KTH dimensional value of the reference sequence;  $z_i(k)$  -- the k-dimensional value of the ith sequence.

#### (2) Calculate the gray correlation coefficient

The reference sequence and the comparison sequence are taken as geometric curves respectively, and the combination of the slopes of the two geometric curves represents the grey correlation coefficient. When analyzing the gray correlation degree of each influencing factor, the gray correlation coefficient of the KTH dimension new data comparison sequence and the reference sequence  $Z_k$  is calculated as follows:

#### (3) Calculate the gray correlation degree

In order to avoid information dispersion and facilitate overall comparison, the correlation coefficient is centrally processed into a single value, that is, the average value of the correlation coefficient between each influencing factor in the newborn comparison series and the use of available energy reference series is calculated, and the corresponding correlation degree calculation formula is obtained as follows:

Among them, the closer the value of correlation degree is to 1, the stronger the correlation is

## **Chapter 5**

### **5.1 Design**

In order to establish a better machine tool use of available energy model, this experiment uses artificial intelligence algorithm to learn machine tool processing parameters in order to establish an use of available energy model. The accuracy of simple BP neural network is low for the model of machine tool modeling analysis, so it cannot establish a more accurate model. Therefore, the factors that can improve the model accuracy in BP neural network are weight matrix, bias value, learning rate and number of training rounds. The initialization parameters of BP neural network have a great impact on the accuracy of its results. Therefore, in this test, after using genetic algorithm to improve the BP neural network, the improved BP neural network is applied to the use of available energy analysis of machine tools, which solves the problems of falling into local optimal solution and difficult to determine the learning rate and the number of training rounds when using BP neural network alone. The weight matrix  $W1$  and  $W2$  bias  $B1$  and  $B2$  in the BP neural network with a hidden layer, as well as the learning rate and training round array, are synthesized into an individual gene. The six variables are randomly combined together through the initialization population operation of the genetic algorithm, and then the optimal initial value generated by algorithm iteration is regarded as the optimal solution. The optimal initialization value is handed over to the BP neural network to train the optimal model.

#### **5.1.1 Design of use of available energy model of GA-BP algorithm**

In genetic algorithm, the individual of population is the initial value of BP neural network, and the individual gene is the weight, bias, learning rate and training round number. The fitness value of an individual is the accuracy rate of the model trained in BP neural network with the initialization parameters corresponding to the individual. The data flow chart of this process is as follows:

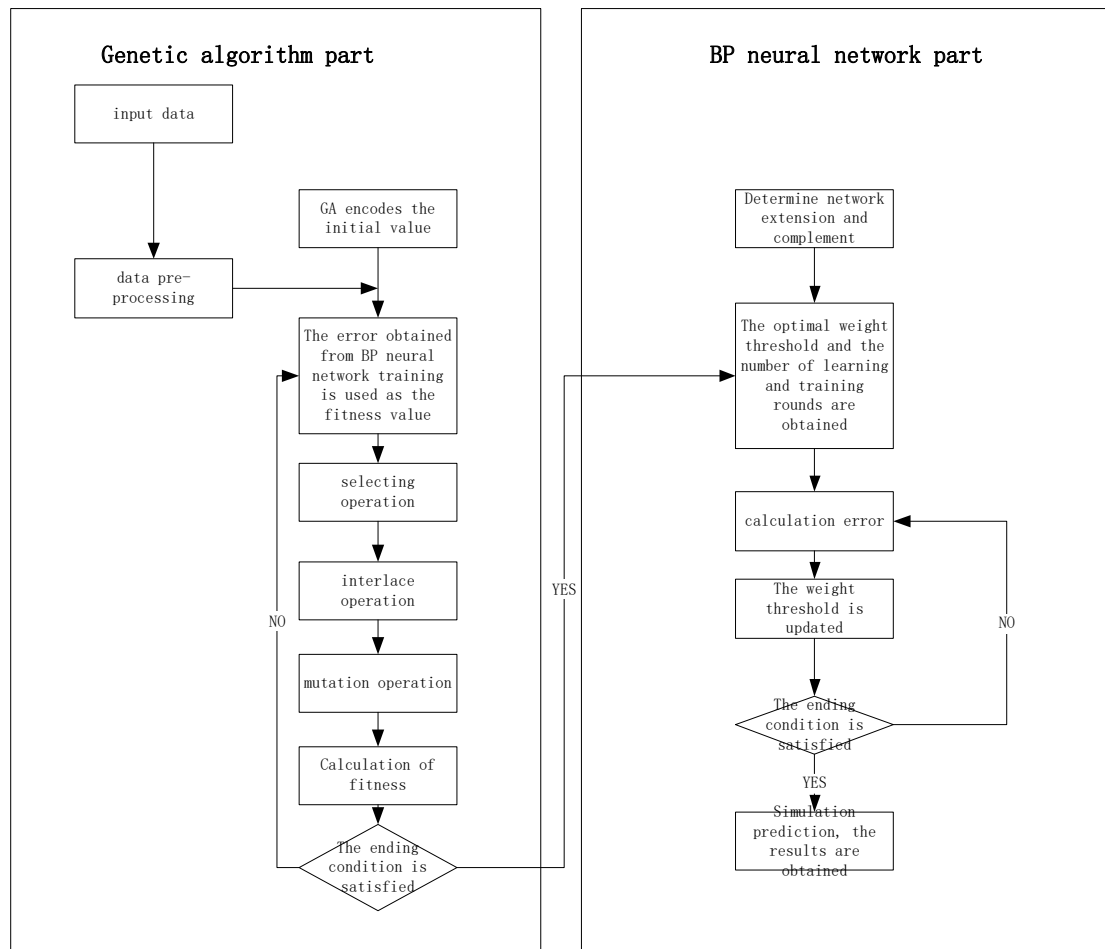


Figure 6 Flow chart of GA optimization BP

When the simple BP neural network is not satisfied with the use scenario, the improved method of genetic algorithm is adopted to achieve a better model to predict the use of available energy of machine tool processing. First determine the number of population in genetic algorithm, and then randomly generated the number of individuals, each individual corresponds to a set of BP neural network parameters, calculating the value of the fitness of each individual, and send them by selecting a series of operation such as crossover and mutation after the fitness of the value of the calculation again, choose the best results. The new generation of individuals will carry out a new round of operation again. After completing all the prescribed rounds, the best individual will be selected and the corresponding parameters of the individual will be handed over to the BP neural network for training. The trained model will be applied to the data of the machine tool, and a result with high accuracy will be obtained at this time.

### 5.1.2 Code design of GA-BP algorithm

The following figure preprocesses the obtained data set. The spindle speed, feed speed, cutting depth and cutting width, namely, the first three columns of the CSV

file of the data set, are taken as the dependent variables of the experiment, while the use of available energy value of the machine tool, namely, the fourth column of the CSV file of the data set, is taken as the result value of the experiment. Because the spindle speed, feed speed, cutting depth, cutting width and the use of available energy of the machine tool differ greatly, the data set is normalized. In the division of the corresponding test set and validation set.

```
learning_rate = 0.05 # Learning Rate
num_of_trian = 2 # Number of training sessions
training_display = 10 # Show how many times per training
data_path = "result" # Model storage path
filename = "newd.csv" # csv data path
v1=[]
x1,y1 = [],[]

#读取csv数据
with open(filename, encoding='UTF-8') as f:
    reader = csv.reader(f)
    for line in reader:
        xt = []
        xt.append(eval(line[0]))
        xt.append(eval(line[1]))
        xt.append(eval(line[2]))
        xt.append(eval(line[3]))
        y1.append([eval(line[4])])
        x1.append(xt)

x1.pop(0)

x_data = np.array(x1)
y_data = np.array(y1)

ss = MinMaxScaler()
x_data = ss.fit_transform(x_data)
y_data = ss.fit_transform(y_data.reshape(-1, 1))
x_data, x_test, y_data, y_test = train_test_split(x_data, y_data, test_size=0.3, random_state=3)
```

Figure 7 Data set preprocessor

After preprocessing the data set, the following figure is based on the algorithm design of the GA model in the GA-BP algorithm model in Figure 5.1.1. The function of the main part is shown in the figure below, including the screening of initial population data, calculation of cumulative probability, rotation selection, hybridization and gene mutation. According to the release speed of computer memory, the population number was set as 50, and 63 chromosomes were selected, crossed and mutated to obtain the optimal gene sequence and optimal individual moderation. The betting wheel algorithm is used for 10 rounds of calculation, and the optimal parameters of BP neural network, namely the paranoid amount, weight and learning rate, are placed in the matrix of the output results, and the maximum accuracy is placed in the last column of the matrix. See the appendix for details of the subroutine.

```

learning_rate = 0.05 # Learning Rate
num_of_trian = 2 # Number of training sessions
training_display = 10 # Show how many times per training
data_path = "result" # Model storage path
filename = "newd.csv" # csv data path
v1=[]
x1,y1 = [[]],[]

#读取csv数据
with open(filename, encoding='UTF-8') as f:
    reader = csv.reader(f)
    for line in reader:
        xt = []
        xt.append(eval(line[0]))
        xt.append(eval(line[1]))
        xt.append(eval(line[2]))
        xt.append(eval(line[3]))
        y1.append([eval(line[4])])
        x1.append(xt)

x1.pop(0)

x_data = np.array(x1)
y_data = np.array(y1)

ss = MinMaxScaler()
x_data = ss.fit_transform(x_data)
y_data = ss.fit_transform(y_data.reshape(-1, 1))
x_data, x_test, y_data, y_test = train_test_split(x_data, y_data, test_size=0.3, random_state=3)

```

Figure 8 GA algorithm body function part

Function part of the BP neural network as shown in the figure below, the GA algorithm in the process of implementation for this part of the subroutine call, the part of the program design of the input layer design as shown in the figure below, including four lines 10 column of neuron structure, a line of ten columns of the hidden layer offset structure, the output layer ten lines of a column of weighting matrix and a row of column structure of paranoia

```

# Input layer
with tf.name_scope("inputs"):
    xs = tf.placeholder(tf.float32, [None, 4], name="x_input")
    ys = tf.placeholder(tf.float32, [None, 1], name="y_input")

    W1temp1 = pop1[:40]
    W1 = tf.constant(W1temp1, shape=[4, 10])
    W1 = tf.Variable(W1)

    b1temp1 = pop1[50:60]
    b1 = tf.constant(b1temp1, shape=[1, 10])
    b1 = tf.Variable(b1)

    W2temp1 = pop1[40:50]
    W2 = tf.constant(W2temp1, shape=[10, 1])
    W2 = tf.Variable(W2)

    b2temp1 = pop1[60]
    b2 = tf.constant(b2temp1, shape=[1, 1])
    b2 = tf.Variable(b2)

```

```

# Hidden layers
with tf.name_scope('hidden_layer'): # Hidden layers. Putting together hidden layer weights, biases, and net inputs
    with tf.name_scope('weight'): # Weighting
        # W1 = tf.Variable(tf.random_normal([4, 10])) # A random normal distribution with ten columns in a row. That is, ten neurons
        tf.summary.histogram('hidden_layer/weight', W1)
    with tf.name_scope('bias'): # Offset
        # b1 = tf.Variable(tf.zeros([1, 10]))
        tf.summary.histogram('hidden_layer/bias', b1)
    with tf.name_scope('Wx_plus_b'): # Net input
        Wx_plus_b1 = tf.matmul(xs, W1) + b1
        tf.summary.histogram('hidden_layer/Wx_plus_b', Wx_plus_b1)
output1 = tf.nn.softplus(Wx_plus_b1) # Activation function relu smoothing version

```

Figure9 BP algorithm body function part

The last section of BP program is to calculate the interpolation between the actual value and the predicted value of the experiment to obtain the corresponding loss function and prediction accuracy. The implementation of the specific program is shown in Figure 10 below:

```

with tf.name_scope('hidden_layer'): # Hidden layers. Putting together hidden layer weights, biases, and net inputs
    with tf.name_scope('weight'): # Weighting
        # W1 = tf.Variable(tf.random_normal([4, 10])) # A random normal distribution with ten columns in a row. That is, ten neurons
        tf.summary.histogram('hidden_layer/weight', W1)
    with tf.name_scope('bias'): # Offset
        # b1 = tf.Variable(tf.zeros([1, 10]))
        tf.summary.histogram('hidden_layer/bias', b1)
    with tf.name_scope('Wx_plus_b'): # Net input
        Wx_plus_b1 = tf.matmul(xs, W1) + b1
        tf.summary.histogram('hidden_layer/Wx_plus_b', Wx_plus_b1)
    output1 = tf.nn.softplus(Wx_plus_b1) # Activation function relu smoothing version

# Output layer
with tf.name_scope('output_layer'): # Output layer. Putting together output layer weights, bias, net input
    with tf.name_scope('weight'): # Weighting
        # W2 = tf.Variable(tf.random_normal([10, 1]))
        # print(W2)
        tf.summary.histogram('output_layer/weight', W2)
    with tf.name_scope('bias'): # Offset
        # b2 = tf.Variable(tf.zeros([1, 1]))
        tf.summary.histogram('output_layer/bias', b2)
    with tf.name_scope('Wx_plus_b'): # Net input
        Wx_plus_b2 = tf.matmul(output1, W2) + b2
        tf.summary.histogram('output_layer/Wx_plus_b', Wx_plus_b2)
    output2 = Wx_plus_b2

```

## 5.2 Implementation

In the algorithm optimization process of 5.1.2 above, the neural network is affected by input and threshold, and the genetic algorithm mainly improves the artificial neural network in these two aspects. There is no mistaking the fact that the units of these input and output variables are completely distinct from one another. The initial input and output data from the experiment should be normalized first in order to eliminate the potential for bias caused by the use of a variety of unit types. In this experiment, the BP neural network with one hidden layer structure is adopted. In the hidden layer, the neuron structure with four rows and ten columns is used, that is, 40 neurons, and the hidden layer bias structure is one row and ten columns. The weight matrix of the output layer adopts the structure of ten rows and one column, and the output layer is biased into the structure of one row and one column. The genetic algorithm is used to select and cross-mutate the 63 values to find the individual with the highest fitness value, and then the genotype of the individual, namely the weight matrix, bias, learning rate and the number of training rounds, is brought into the BP neural network to obtain the optimal model.

### 5.2.1 Experimental data set

In this experiment, a model for predicting machine tool use of available energy is established based on spindle speed, feed speed, cutting depth and cutting width. The data are from [5] and shown in Table 4.1.

Table 2 Data set details

| n(r/min) | f(mm/min) | ap(mm) | ae(mm) | EC(KJ)  |
|----------|-----------|--------|--------|---------|
| 1000     | 200       | 0.2    | 5      | 555.802 |
| 1000     | 200       | 0.3    | 10     | 204.929 |
| 1000     | 200       | 0.4    | 15     | 108.519 |
| 1000     | 250       | 0.2    | 5      | 446.109 |
| 1000     | 250       | 0.3    | 10     | 166.050 |
| 1000     | 250       | 0.4    | 15     | 89.823  |
| 1000     | 300       | 0.2    | 5      | 381.832 |
| 1000     | 300       | 0.3    | 10     | 142.976 |
| 1000     | 300       | 0.4    | 15     | 73.988  |
| 1500     | 200       | 0.2    | 5      | 357.042 |
| 1500     | 200       | 0.3    | 10     | 162.727 |
| 1500     | 200       | 0.4    | 15     | 319.031 |
| 1500     | 250       | 0.2    | 5      | 289.604 |
| 1500     | 250       | 0.3    | 10     | 133.648 |
| 1500     | 250       | 0.4    | 15     | 258.476 |
| 1500     | 300       | 0.2    | 5      | 233.559 |
| 1500     | 300       | 0.3    | 10     | 112.551 |
| 1500     | 300       | 0.4    | 15     | 213.109 |
| 2000     | 200       | 0.2    | 5      | 264.303 |
| 2000     | 200       | 0.3    | 10     | 445.797 |
| 2000     | 200       | 0.4    | 15     | 185.620 |
| 2000     | 250       | 0.2    | 5      | 213.939 |
| 2000     | 250       | 0.3    | 10     | 358.579 |
| 2000     | 250       | 0.4    | 15     | 151.343 |
| 2000     | 300       | 0.2    | 5      | 180.886 |
| 2000     | 300       | 0.3    | 10     | 306.850 |
| 2000     | 300       | 0.4    | 15     | 128.147 |

### 5.2.2Parameter determination

In order to obtain all the optimal values as much as possible, the initial test values of BP neural network are initialized to random values through genetic algorithm, and the given crossover probability (PC) is 0.8 and mutation probability (PM) is 0.1. Considering the performance of the running machine, the total number of populations is not set too high in this experiment.

Table 3 Algorithm parameter setting

| Algorithms | Parameters                                                 |
|------------|------------------------------------------------------------|
| GA         | pop_size=50, chromosome_length=63, iter=20, pc=0.8, pm=0.1 |

Considering that iterative operation of genetic algorithm cannot release memory space well when optimizing BP neural network, the number of initial populations is

set to 50 and the number of iterations is set to 20 in this experiment. The optimal individual in each generation is stored, and if the fitness value of the optimal individual in the next generation generated by the genetic algorithm is higher than that of the previous generation, it will be replaced.

### 5.3 Summary

The prediction accuracy of the model trained by BP neural network based on the optimal initialization parameter values selected by genetic algorithm is 94.6%. However, after ten times of random initialization parameter value training, the average accuracy of the simple BP neural network is only 81.7%. It can be seen that it is practical and effective to optimize BP neural network by genetic algorithm to model machine tool use of available energy.

## Chapter 6

### 6.1 Result

After using genetic algorithm to improve BP neural network, although good prediction accuracy has been obtained in the modeling and analysis process experiment of machine tools, in order to further improve the accuracy, this chapter will describe how to improve the accuracy of the algorithm by improving the initialization of the population in the genetic algorithm.

#### 6.1.1 Optimization of initialization values

According to the result of 5.1.2 part of the program content to realize the display as shown in the figure below, a total of 10 rounds of betting on calculation of wheel method algorithm, optimized the optimal results of the experiment precision of GA - BP in the fifth round of the operation of the program results are as follows, it just vector data set down when is 0.13, the number of iterations is 4672, the optimal prediction accuracy is 97.0; The specific weight matrix and paranoia amount are shown in the figure below:

```
Here is the value of boj_value
[78.0, 78.0, 77.0, 77.0, 89.0, 64.0, 97.0, 81.0, 77.0, 76.0, 92.0, 91.0, 81.0, 84.0, 89.0, 42.0, 77.0, 85.0, 65.0, 69.0, 66.0, 68.0, 79.0, 84.0, 50.0, 88.0, 78.0, 73.0, -147.0, 94.0, 60.0, 74.0, 82.0, 68.0, 80.0, 87.0, 77.0,
[0.14922054, -1.36850002, -1.63785165, -0.91431934, 0.88834072, -0.68319409, 1.68888837, 2.09272623, -2.06433268, -0.13314207, -1.5057587, -1.39701533, 0.82636235, -2.51355982, -2.67659856, -0.2227443, 0.6296871, 2.63612424,
results: [[1.39270831, 1.43972334, 1.39340704, -0.96416645, 2.43709632, -0.86560481, -2.10974896, -0.53473173, -0.74603495, 1.47492831, 0.84556012, 2.96898321, -0.20433159, -1.4487567, 1.50644609, -2.32845335, -0.45458307, -2.96265702,
50
Complete the first 10 round
[[1.39270831, 1.43972334, 1.39340704, -0.96416645, 2.43709632, -0.86560481, -2.10974896, -0.53473173, -0.74603495, 1.47492831, 0.84556012, 2.96898321, -0.20433159, -1.4487567, 1.50644609, -2.32845335, -0.45458307, -2.96265702,
the len of results 10
The optimum fitness value is 97.0
Optimal parameters are [0.14922054, -1.36850002, -1.63785165, -0.91431934, 0.88834072, -0.68319409, 1.68888837, 2.09272623, -2.06433268, -0.13314207, -1.5057587, -1.39701533, 0.82636235, -2.51355982, -2.67659856, -0.2227443,
Process finished with exit code 0
```

Figure10 Optimal parameter results after GA-BP algorithm optimization

### 6.1.1 Optimization of initialization values

In the training process, BP neural network adjusts the weight matrix and bias by gradient descent method, which is just like a person going down a mountain. Step by step from the top to the foot of the mountain. The choice of road depends on the initialized weight matrix value and bias value as well as the error returned by the output layer, but the same person from different positions at the top of the mountain down the road is also different, so it is also crucial to choose the starting point of the mountain (weight matrix and bias initialization value)

### 6.1.2 Optimization of initialization values

Considering that each result of this experiment has certain randomness, the results of ten times are used to illustrate the problem. The following images are obtained by running the data of BP neural network ten times, optimizing the data of BP ten times with GA and optimizing the data of GA-BP ten times after GA initialization value.

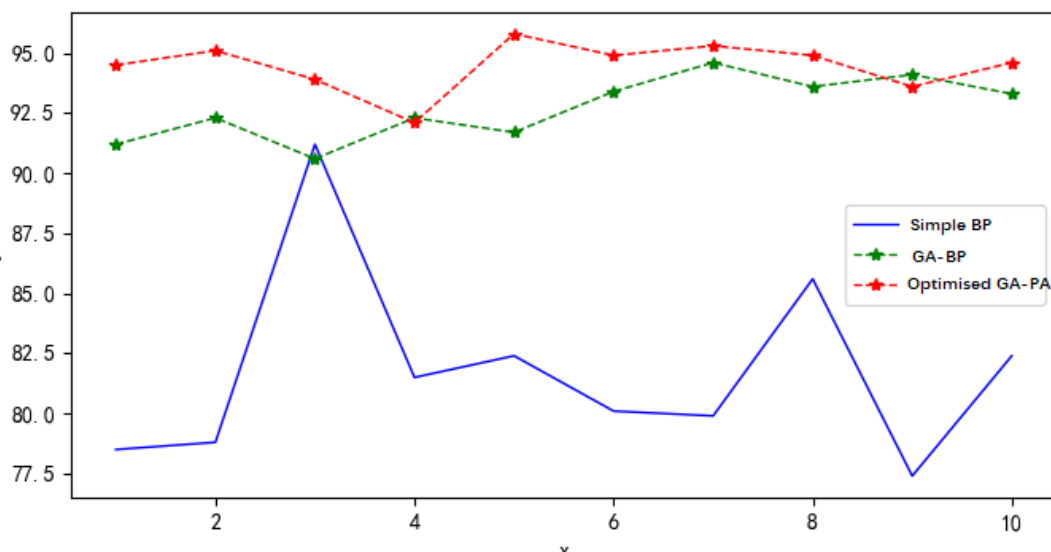


Figure11 Precision comparison plot for each number of rounds

It can be seen from the broken line in the above figure that although the BP neural network has achieved more than 90% accuracy in a training result, the broken line is extremely unstable, and the GA-BP algorithm, which optimizes the initial weight, performs best and obtains the largest extreme value of 95.8.

After adjusting the range of individual genotypes in the initialization population of the GA, it is found that the weight matrix and the initialization values with bias in the

range of negative three to positive three have higher accuracy under the same number of iterations and the number of populations

## **Chapter 7**

### **7.1 Conclusion**

In the development of industry 4.0 era, CNC machine tools are widely used in the manufacturing industry. In this experiment based on the optimization of the process, the genetic algorithm constantly trained produced a set of optimal parameter value, through to the expression of weighting matrix, the optimal individual bias, vector and the number of train wheel, through within the scope of the negative is three to three after initialization weight matrices and bias, obtained the higher accuracy of the initial value, The test accuracy of the model obtained by BP neural network after these data training is 95.8%, which is far greater than the accuracy of BP neural network training 10 times on the data. It can be concluded that the method is obviously better than BP neural network in predicting the use of available energy of machine tools. The research results of this paper can be summarized as follows: using regression model analysis and GA-BP to optimize the input and parameters of neural network; The neural network with optimal weight bias learning rate and number of training rounds can provide better use of available energy prediction than the simple BP neural network with random parameters. The model developed in this study can further optimize the processing parameters to achieve the purpose of energy saving.

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